Conventions, Accuracy Metrics, Classification, Regression

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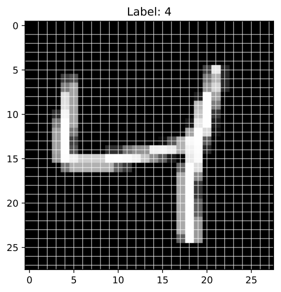
Outline

1. Introduction to Machine Learning
2. Machine Learning Fundamentals
3. Classification vs Regression
4. Evaluation Metrics
5. Advanced Topics

Digit Recognition Problem

Let us work on the digit recognition problem.

Notebook: rule-based-vs-ml.html



Rule-based Approach for Digit Recognition

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- There can be some cases of 4 where the first $|$ is at 45 degrees
- There can be some cases of 4 where the width of each stroke is different

Pop Quiz: Rule-Based vs ML

Quick Quiz 1

Why is it difficult to write rules for digit recognition?

a) Digits are always the same

Answer: b) Handwriting variations make rule-based approaches extremely complex!

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a) Digits are always the same
b) Variations in handwriting, rotation, thickness make rules complex
c) Rules are faster than ML

Answer: b) Handwriting variations make rule-based approaches extremely complex!

Apple Quality Features

- Size

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Should We Include Sample Numbers?

Answer: Usually no! Sample numbers are typically arbitrary identifiers and not meaningful features. Let us remove it.

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Let us modify our data table for now.

Colour	**Size**	**Texture**	**Condition**
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad

Training Set Components

The training set consists of two parts:

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2. Output or Response Variable

Dataset Notation

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2. Output vector ($\mathbf{y} \in \mathbb{R}^{n}$) containing output variable for n samples.

Dataset Example

Example (after encoding): $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ (Orange=1, Small=0, Smooth=1)

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- Complete dataset: $\mathcal{D} = \{(\mathbf{x}_i^\top, y_i)\}_{i=1}^n$

Machine Learning Goal

Learn f: Condition $= f$(colour, size, texture)

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1. From Training Dataset
2. To Predict the condition for the Testing set

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A: Ideally, no!

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- Ideally - we want to predict "well" on all possible inputs. But, can we test that?
- No! Since, the test set is only a sample from all possible inputs.

Training vs Test Sets

Both the training set and the test set are samples drawn from the hidden true distribution (also sometimes called population)

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More discussion later once we study bias and variance

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# People	Temp (C)	Energy (kWh)
4000	30	30
4200	30	32
4200	35	40
3000	20	?
1000	45	?

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a) Sample ID numbers

Answer: b) Features should be meaningful and related to what you're predicting!

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a) Sample ID numbers
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Answer: b) Features should be meaningful and related to what you're predicting!

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    - How much energy will campus consume?
    - How much rainfall will fall?

Pop Quiz: Problem Types

Quick Quiz 3

Predicting house prices is an example of:

a) Classification (discrete output)

Answer: b) Regression - house prices are continuous values!

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b) Regression (continuous output)
c) Neither

Answer: b) Regression - house prices are continuous values!

Accuracy Calculation

$$\text{Accuracy} = \frac{|\{i : y_i = \hat{y}_i\}|}{n} = \frac{3}{5} = 0.6$$

Accuracy Notation

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- **Alternative: Indicator function notation**

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} \mathbf{1}[y_i = \hat{y}_i]}{n}$$

where $\mathbf{1}[\text{condition}] = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$

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- Both notations are mathematically equivalent and commonly used in ML literature

When Precision/Recall Matter

Cases for this:

- Cancer Screening

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- Planet Detection

Precision Metric

$$\text{Precision} = \frac{|\{i : y_i = \hat{y}_i = \text{Good}\}|}{|\{i : \hat{y}_i = \text{Good}\}|} = \frac{2}{4} = 0.5$$

Definition: "The fraction of relevant instances among the retrieved instances"
In simple terms: Out of all times we predict "Good", how many times is it actually "Good"?

Accuracy vs Precision/Recall

$$\text{Accuracy} = \frac{98}{100} = 0.98$$
$$\text{Recall} = \frac{0}{1} = 0$$
$$\text{Precision} = \frac{0}{1} = 0$$

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

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Each cell represents a different type of prediction outcome:

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- FN: Missed a positive (dangerous!)

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Each cell represents a different type of prediction outcome:

- TP: Correctly predicted positive
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- FN: Missed a positive (dangerous!)
- TN: Correctly predicted negative

Precision: "How accurate are my positive predictions?"

		Ground Truth	
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$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{\text{Correct Positives}}{\text{All Predicted Positives}}$$

Precision: "How accurate are my positive predictions?"

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Focus: Look at the PREDICTED POSITIVE ROW

Question: When I predict "positive", how often am I right?
Answer: Out of all my positive predictions (TP + FP), TP are correct.

Recall: "How many actual positives did I find?"

		Ground Truth	
		Positive	Negative
Predicted	Positive	**TP**	FP
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$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{Correct Positives}}{\text{All Actual Positives}}$$

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		Positive	Negative
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$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{Correct Positives}}{\text{All Actual Positives}}$$

Focus: Look at the ACTUAL POSITIVE COLUMN

Question: Of all things that ARE positive, how many did I catch?
Answer: Out of all actual positives (TP + FN), I found TP of them.

Example: Medical Diagnosis

Let's say we're testing for a disease:

		Actually Has Disease	
		Yes	No
Test Says	Positive	**90**	**10**
	Negative	**5**	**895**

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$$\text{Accuracy} = \frac{\boxed{90} + \boxed{895}}{1000} = 0.985\ (98.5\%)$$

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Mean Error Issues

Is there any downside with using mean error?

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Pop Quiz: Metrics Choice

Quick Quiz 4

For cancer detection (1 positive case in 1000), which metric is most important?

a) Accuracy only

Answer: b) Recall - we cannot afford to miss cancer cases!

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c) Speed of prediction

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Which metrics should you use for imbalanced datasets?

1. Accuracy only

Answer: c) Precision, recall, and F1-score give a more complete picture!

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- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score

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  ML learns rules from data, traditional programming uses predefined rules
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- **Use baselines:**
  Simple baseline models help validate your approach

Summary: Evaluation Metrics

Task	Common Metrics	When to Use
Classification	Accuracy, Precision, Recall, F1 Confusion Matrix	Balanced/Imbalanced data Multi-class problems
Regression	MSE, RMSE, MAE Mean Error	Continuous predictions Check for bias

Remember

Choose metrics based on your problem's characteristics and business requirements!